Westfälische
Wilhelms-Universität
Münster

Economics of Cybercrime

The Influence of Perceived Cybercrime Risk on Online Service Adoption of European Internet Users

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June 23, 2014

Agenda

A. Perceived Cybercrime Risk and Online Service Adoption
B. The “Technology Avoidance Model”
C. Data and Methodology
D. Results
E. Conclusions

Cybercrime Risk and Online Service Adoption

Online services provide extensive **economic** and **social benefits**

- Less expensive, more convenient, faster, higher product variability and availability

Anderson et al. (2013) [1]

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Consumer-oriented cybercrime is a threat to these benefits

- Indirect costs of cybercrime are the largest amount
- Indirect costs are driven by online service avoidance

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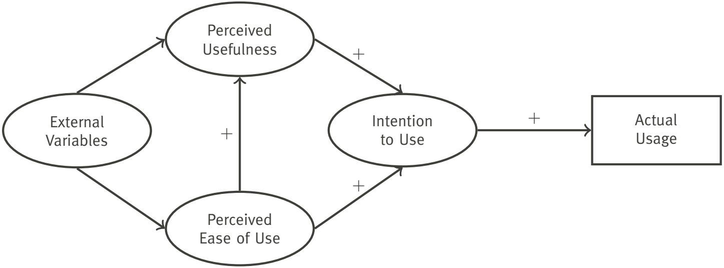
Research Question: What makes Internet users hesitate ?

- Validate influence of perceived cybercrime risk on avoidance
- Investigate antecedents of perceived cybercrime risk
- Look how different types of users perceive risk

Anderson et al. (2013) [1]

Acceptance Models for Online Services

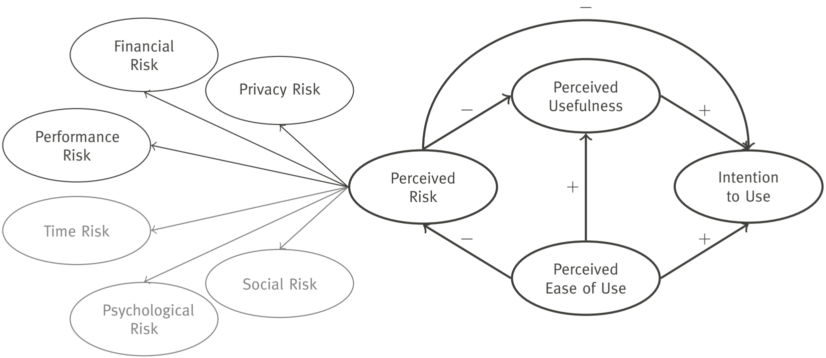
Technology Acceptance Model (TAM)



Venkatesh & Davis (1996) [5]

Acceptance Models for Online Services

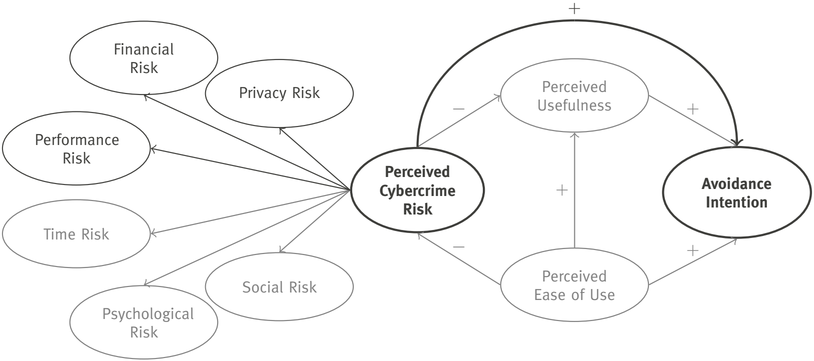
TAM extended with Perceived Risk



Featherman & Pavlou (2003) [3]

Acceptance Models for Online Services

Cybercrime perspective on online service avoidance



Antecedents of Perceived Risk of Cybercrime

Risk perception of traditional (offline) crime

- Prior victimization increases perceived risk
- Media reports increase perceived risk

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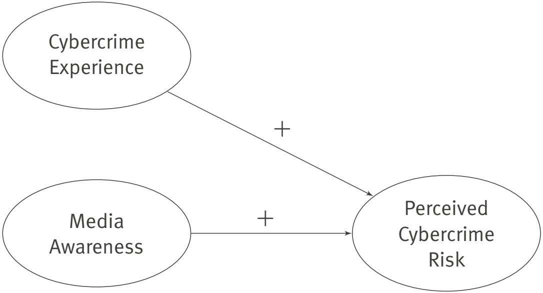
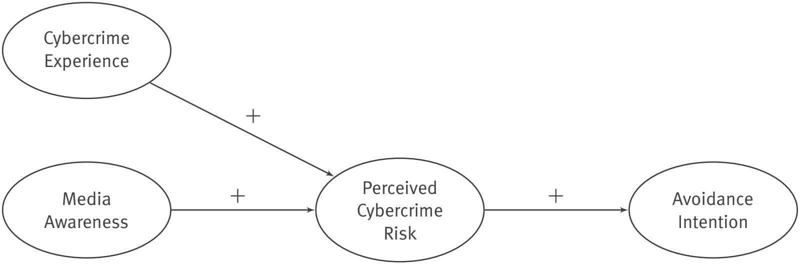


The “Technology Avoidance Model”



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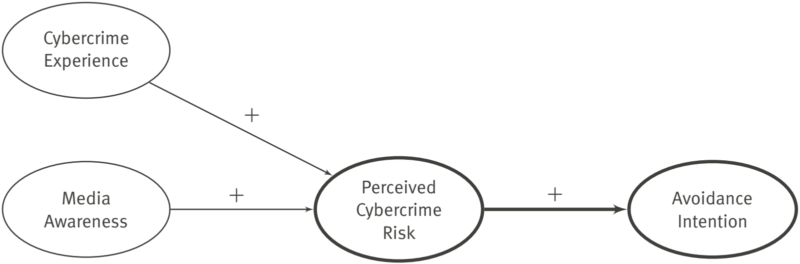

- *Perceived Cybercrime Risk* increases *Avoidance Intention*

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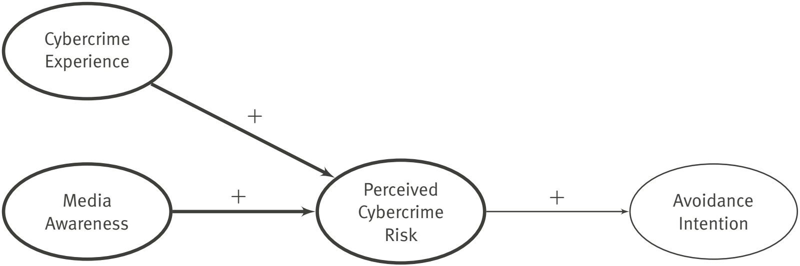

- *Perceived Cybercrime Risk* increases *Avoidance Intention*
- *Cybercrime Experience* and *Media Awareness* increase *Perceived Cybercrime Risk*

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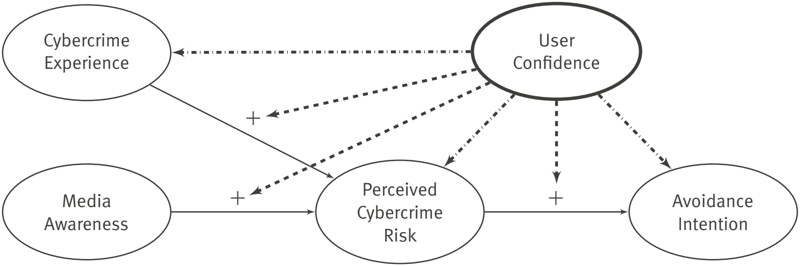

- *Perceived Cybercrime Risk* increases *Avoidance Intention*
- *Cybercrime Experience* and *Media Awareness* increase *Perceived Cybercrime Risk*
- *User Confidence* moderates the effects and latent variables

Eurobarometer 390 Cyber Security Report

Report on **Internet usage** and **security concerns** of EU citizens

- Commissioned by the European Commission
- Conducted in **2012** in all 27 member states
- 26,593 responses

Representative sample of **EU Internet users** above the age of 15

- ~ 1,000 responses per country
- Random route and closest birthday rules within countries
- Stratification by country

Internet users ~ 18,000 (daily access by 53%)

European Commission (2012) [2]

Measurement of constructs

Avoidance Intention of online services

"Due to security concerns I am less likely to use . . . ?"

- Single binary item
- One model per online service

	Currently Using	Avoidance Intention
Online shopping	53%	18%
Online banking	48%	15%
Online social networking*	52%	37%

*Proxy: *"Less likely to give personal information on websites"*

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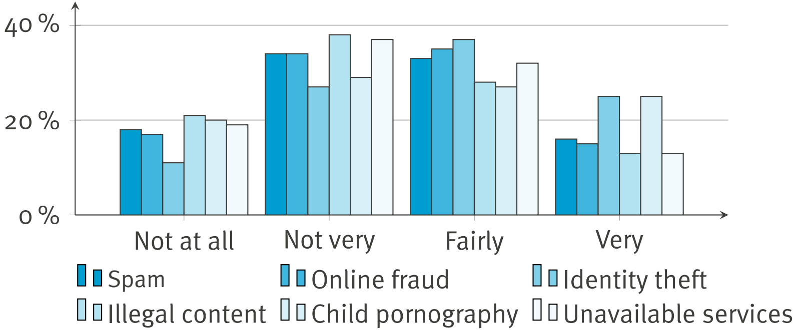
Measurement of constructs

Perceived Cybercrime Risk

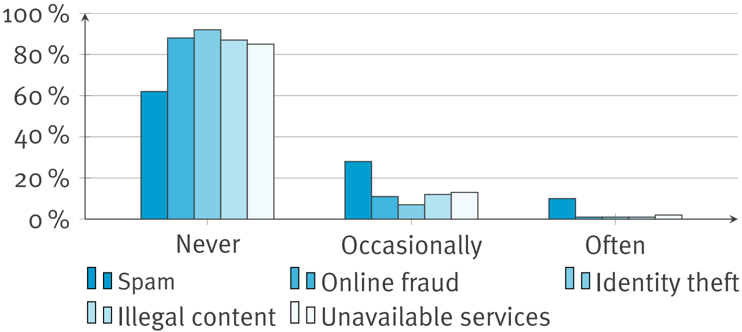
“How concerned are you personally about becoming a victim of or encountering . . . ?”



Measurement of constructs

Cybercrime Experience

"How often have you experienced or been victim of one of the following situations . . . ?"



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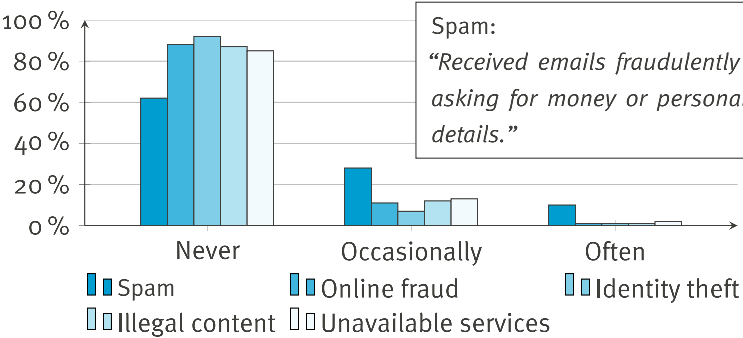
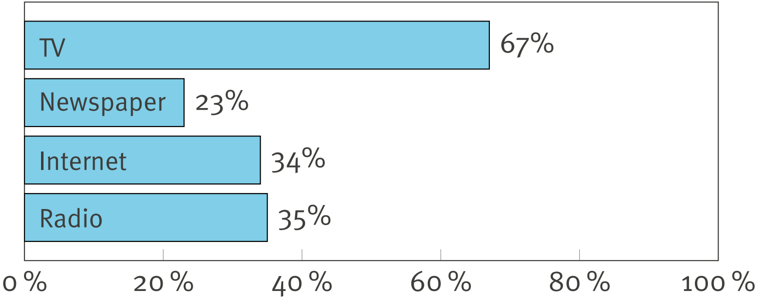


Spam:
"Received emails fraudulently asking for money or personal details."

Measurement of constructs

Media Awareness

"In the last year have you heard anything about cybercrime from one of the following sources . . . ?"



Methodology

Secondary analysis using Structural Equation Modelling (SEM)

	Benefits	Limitations
Secondary analysis	Representative sample; Sophisticated surveying process;	Available questions; Short answer scales; Unvalidated measurement scales; Heterogeneous data;
SEM	Categorical indicators; Sampling weights; Missing values; Model fit indices;	

Muthen et al. (1997) [4]

SEM Results (Path Analysis)

Impact of Perceived Cybercrime Risk (PCR) on Avoidance Intention (AI)

		Model fit			
Online service	PCR – AI	TLI	CFI	RMSEA	$\chi^2(df)$
Online shopping	0.167^{***}	.991	.993	.010	131(51)
Online banking	0.093^{***}	.990	.993	.010	143(51)
Social networking	0.061^{*}	.985	.988	.013	202(51)
Thresholds for good model fit		$> .950$	$> .950$	$< .050$	

Significance levels: ***: $p < 0.001$; *: $p < 0.05$

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- Social network avoidance is better explained by privacy risk

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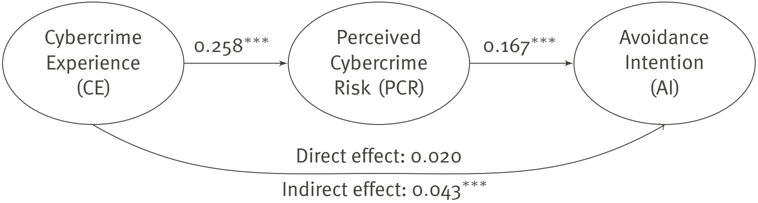
- Social network avoidance is better explained by privacy risk
- Online shopping includes the highest amount of uncertainty
- Online banking based on consumer loyalty and trust

SEM Results (Path Analysis)

Avoidance Intention of **online shopping**:



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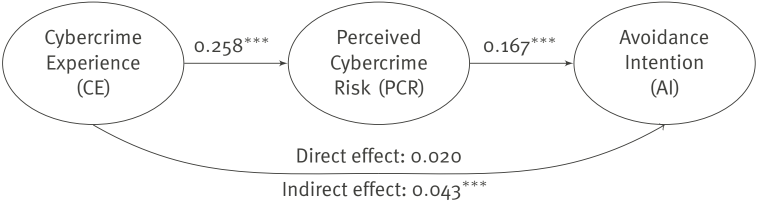

	CE – PCR	CE – AI		
Online Service		Direct	Indirect	**Mediation**
Online shopping	0.258***	0.020	0.043***	**Full**
Online banking	0.258***	0.142***	0.024***	**Partial**
Social networking	0.258***	0.121***	0.016*	**Partial**

SEM Results (Moderation Analysis)

Multi-group analysis based on the confidence level in conducting online transactions

	Confident	Inconfident
# Respondents	4,972	2,196
Effects	invariant	invariant
Perceived Cybercrime Risk Level	Low	High
Level of Avoidance Intention*	Low	High
Level of Cybercrime Experience	High	Low

*only for online shopping and online social networking

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The risk perception of inconfident Internet users is influenced by missing factors in the model

Conclusions

What makes Internet users hesitate ?

Perceived cybercrime risk increases online service avoidance

- Effect found for all three online services
- Strongest effect for online shopping avoidance

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Further investigation of risk antecedents is needed

- Cybercrime experience increases perceived risk of cybercrime
- Media awareness not included

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User characteristics matter

- Unconfident users perceive more cybercrime risk
- and have a higher avoidance intention

Sources

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Confirmatory factor analysis

Latent Variable	Indicator	Mean	SD	Loading	SE	Z-Score	R^2
Media Awareness	QE8.1	0.67	0.47	0.540***	0.041	13.315	0.292
	QE8.2	0.23	0.42	0.729***	0.026	27.788	0.531
	QE8.3	0.34	0.47	0.719***	0.020	35.891	0.517
	QE8.4	0.35	0.48	0.698***	0.026	26.835	0.487
Cybercrime Experience	QE10.1	0.09	0.32	0.681***	0.039	17.293	0.464
	QE10.2	0.49	0.68	0.624***	0.025	25.007	0.389
	QE10.3	0.14	0.38	0.701***	0.025	28.475	0.491
	QE10.4	0.17	0.43	0.707***	0.040	17.622	0.500
	QE10.5	0.14	0.38	0.754***	0.036	21.198	0.569
Perceived Cybercrime Risk	QE11.1	2.74	0.97	0.821***	0.007	114.124	0.674
	QE11.2	2.45	0.98	0.821***	0.008	99.549	0.674
	QE11.3	2.45	0.97	0.805***	0.010	77.395	0.648
	QE11.4	2.54	1.09	0.801***	0.009	86.913	0.642
	QE11.5	2.31	0.98	0.823***	0.007	124.904	0.677
	QE11.6	2.32	0.99	0.795***	0.007	119.106	0.632
AI: Online Banking	QE7.2	0.18	0.38				
AI: Online Shopping	QE7.1	0.15	0.35				
AI: OSN	QE7.3	0.37	0.48				

$\chi^2(df) = 448.73\ (123)$ p<.05 = 0 RMSEA = .012 TLI = .961 CFI = .968

Validity analysis

	CR	AVE	MA	CE	PCR	AI: OS	AI: OB	AI: OSN
Media Awareness (MA)	0.77	0.46	**0.678**	(0.022)	(0.038)	(0.035)	(0.028)	(0.025)
Cybercrime Experience (CE)	0.82	0.48	0.322***	**0.693**	(0.021)	(0.044)	(0.033)	(0.013)
Perc. Cybercrime Risk (PCR)	0.92	0.66	0.008	0.264***	**0.812**	(0.019)	(0.017)	(0.028)
AI: Online Shopping (OS)	-	-	0.028	0.061	0.170***	-	(0.035)	(0.032)
AI: Online Banking (OB)	-	-	0.034	0.172***	0.127***	0.577***	-	(0.05)
AI: OSN	-	-	0.329***	0.152***	0.092***	0.305***	0.296***	-

Lower-left: between construct correlations; Diagonal: $\sqrt{AVE}$; Upper-right: SE's of the correlations.
Avoidance Intention (AI), Online Social Networking (OSN)

Modification indices

Cross-loadings of Media Awareness

Latent Variable	Operator	Indicator	MI	EPC	Std.EPC
Media Awareness	BY	QE10.2	85.39	0.608	0.328
Cybercrime Experience	BY	**QE8.4**	55.66	0.348	0.237
Media Awareness	BY	QE10.1	34.32	−0.409	−0.221
Cybercrime Experience	BY	**QE8.3**	28.46	−0.276	−0.188
Perc. Cybercrime Risk	BY	QE10.2	25.53	−0.152	−0.125
Perc. Cybercrime Risk	BY	**QE8.1**	22.33	0.109	0.090
Media Awareness	BY	QE10.3	22.06	−0.319	−0.172
Perc. Cybercrime Risk	BY	**QE8.3**	11.71	−0.111	−0.091

Confirmatory factor analysis (Reduced model)

Latent Variable	Indicator	Mean	SD	Loading	SE	Z-Score	R^2
	QE10.1	0.09	0.32	0.776^{***}	0.041	19.006	0.602
	QE10.2	0.49	0.68	0.556^{***}	0.025	21.900	0.309
Cybercrime Experience	QE10.3	0.14	0.38	0.769^{***}	0.030	26.030	0.591
	QE10.4	0.17	0.43	0.724^{***}	0.042	17.265	0.524
	QE10.5	0.14	0.38	0.740^{***}	0.046	16.021	0.548
	QE11.1	2.74	0.97	0.821^{***}	0.007	113.882	0.674
	QE11.2	2.45	0.98	0.820^{***}	0.008	99.558	0.672
Perceived Cybercrime Risk	QE11.3	2.45	0.97	0.805^{***}	0.010	77.593	0.648
	QE11.4	2.54	1.09	0.801^{***}	0.009	86.910	0.642
	QE11.5	2.31	0.98	0.823^{***}	0.007	124.615	0.677
	QE11.6	2.32	0.99	0.795^{***}	0.007	119.309	0.632
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AI: OSN	QE7.3	0.37	0.48				

N = 17773 $\chi^2\ (df) = 254.07\ (70)\ \chi^2/df = 3.63$ p<0.05 = 0
RMSEA = .012 (.011 – .014) TLI = 0.98 CFI = 0.984

Validity analysis (Reduced model)

	CR	AVE	CE	PCR	AI: OS	AI: OB	AI: OSN
Cybercrime Experience (CE)	0.84	0.51	**0.714**	(0.020)	(0.043)	(0.031)	(0.012)
Perc. Cybercrime Risk (PCR)	0.92	0.66	0.258***	**0.812**	(0.019)	(0.017)	(0.028)
AI: Online Shopping (OS)	-	-	0.063	0.170***	-	(0.035)	(0.032)
AI: Online Banking (OB)	-	-	0.167***	0.127***	0.577***	-	(0.050)
AI: OSN	-	-	0.137***	0.092***	0.305***	0.297***	-

Lower-left: between construct correlations; Diagonal: $\sqrt{\text{AVE}}$; Upper-right: SE's of the correlations.
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Measurement invariance analysis

Model	χ^2 (*df*)	CFI	TLI	RMSEA (90% CI)	$\Delta\chi^2$ (*df*)	Δ*CFI*
Online Banking						
Mod A: Baseline	167.81 (102)	.995	.994	.013 (.009 – .016)		
Mod B: Invariant	213.41 (123)	.993	.993	.014 (.011 – .017)	73.67 (21)	.002
Mod C: Fixed Path Coef.	228.16 (126)	.992	.992	.015 (.012 – .018)	19.46 (3)	.001
Mod D: Fixed Factor Means	265.39 (126)	.990	.989	.017 (.014 – .020)	33.36 (3)	.003
Online Shopping						
Mod A: Baseline	168.25 (102)	.995	.994	.013 (.009 – .017)		
Mod B: Invariant	215.39 (123)	.993	.993	.014 (.011 – .017)	75.03 (21)	.002
Mod C: Fixed Path Coef.	233.62 (126)	.992	.992	.015 (.012 – .018)	20.02 (3)	.001
Mod D: Fixed Factor Means	265.95 (126)	.990	.989	.017 (.014 – .020)	31.57 (3)	.003
Online Social Networking						
Mod A: Baseline	192.78 (102)	.993	.991	.015 (.012 – .019)		
Mod B: Invariant	238.10 (123)	.992	.991	.016 (.013 – .019)	75.05 (21)	.001
Mod C: Fixed Path Coef.	237.59 (126)	.992	.991	.015 (.012 – .018)	09.13 (3)	.000
Mod D: Fixed Factor Means	276.69 (126)	.989	.988	.018 (.015 – .021)	26.86 (3)	.003